Strategy of Detecting Abnormal Behaviors by Fuzzy Logic

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***Abstract* — This work falls within the framework of the video surveillance research axis. This work falls within the scope of video surveillance. It involves a link between automatic processing and problems related to video surveillance. The job is to analyze video streams coming from a network of surveillance cameras, deployed in an area of interest in order to detect abnormal behavior. Our approach in this article relies on the new application and the use of fuzzy logic in the case of division and fusion of the crowd. The detection of these behaviors will increase the speed of response of the security services in order to perform accurate analysis and detection of events in real time.**

***Keywords* — Abnormal behavior detection, crowd, classification, segmentation, tracking, fuzzy logic, circular variance, videos.**

I. Introduction

There has recently been an interest within computer vision in the analysis of densely crowded environments. Problems such as segmenting video into crowd components [1], estimating crowd size [2], determining the goal of individuals within a crowd [3, 4] have all been subjects of research. Most of these efforts are motivated by the ubiquity of surveillance cameras, the challenges of crowd modeling, and the importance of crowd monitoring for various applications. In many of these, the goal is not so much to analyze normal crowd behavior, but to detect deviations from it. These are referred to as anomalous or abnormal events.

The approach suggested in this article differs from the existing approach [5-8] by its dynamic of detecting anomalies, in which it makes the detection of anomalies possible for both cases (case of a group or a single person). It can be divided into three sublevels: the bottom level (the estimate of optical flow), the intermediate level (construction of the model magnitude) and the semantic level (notification of the operator).

The goal of the used approach is the detection of anomalies in very dense scenes based on the speed and orientation of the individuals and that of the group. The various anomalies are detected using fuzzy logic as a method of automatic classification of crowd behavior, for the management of anomalies in a group of people.

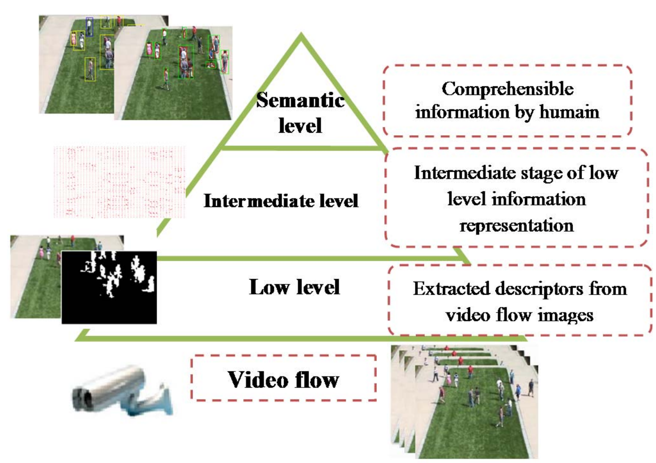

Fig. 1. Global illustration of our solution for the crowd behavior analysis.

The remainder of this paper is organized as follows: in section II we present a short background on the various approaches as well as the works related to this field. We illustrate in section III the suggested approach in order to deal with certain problems encountered in the literature. Section IV presents the mathematical formulation of the various methods used in order to detect anomalies in a crowded scene. Finally, the results are presented in section V and we will finish by a conclusion of the work that has been done, as well as prospects for future work.

II. Related work

The Approaches used for the analysis of crowd behavior in video sequences generally comprise four essential stages:

Detection of movement, segmentation, classification, and tracking [8-13].

Whereas the temporal derivative quantifies the variation of the aspect of each pixel considered individually in the

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movement detection case, the optical flow is modeled by a vector field in two dimensions representing the projection on the image plane of the real movement observed (in 3D). Accordingly of many Methods [14, 15, and 16] were proposed since the precursory article of Horn and Schunck [17] with an aim of improving the implementation of the latter. In [18], nine algorithms are studied and compared according to criteria of precision and density of the obtained vector field, but no mention is made of algorithmic complexity. The work of [19] makes it possible to fill this gap by measuring the reports/ratios (precision) / (calculations team) of these methods.

The segmentation is the stage which consists of cutting out the image in a successive way by considering the apparent movement dominating the zones not labeled then by detecting the zones not conforming to this model of movement [20]. The principle of this method rests on the taking into account of a total image in which the dominant movement and the zones in conformity with this movement forming a first area of the partition are estimated. This process of estimate and detection is reiterated on the non-conforming zones until all pixels are classified [21, 22].

The method of training for a phase of classification generates a function which corresponds to an image received in a specific label entry. There are several methods of training in literature, such as decision trees [23], neural networks [24], fuzzy logic, AdaBoost (Adaptive Boosting) [25], or machines with vectors of support (MVS) [26].

The methods of tracking propose to recognize and locate in the course of time the objects present in a temporal sequence of images [27, 28]. Within the framework of a human crowd, they find a particular interest in video monitoring where the follow-up of the individuals makes it possible to automatically control the comings and goings in a space. Just like recognition starting from an image, the continuation? can be based on graphic properties such as colors or contours [29, 30]. Moreover, adding a temporal dimension makes it possible to suppose a continuity of the presence and position of the objects in the scene, in spite of screenings. The temporal and space consistency of the followed? characteristics can in certain cases be obtained using methods of partitioning (clustering) [31].

In our work, we propose the use of the detection movement technique by optical flow. The latter there's only one makes it possible to detect groups that move in the same direction and to extract the reasons for movement. The major advantage of this method is that it doesn't need to be modeled [6], because it consists in detecting the movement by calculation in any point of the image of a mathematical quantity which is a function of the intensity or the color of the whole of the pixels and which is supposed to reflect the importance of the visible movement in the scene. We propose thereafter the segmentation by regrouping of the areas with an aim of providing a more precise cutting of the borders of the areas. Thereafter, we propose to use a technique of fuzzy logic, in the case of division and fusion of the crowd.

III. PROPOSED SCHEME

The principal stages of the suggested approach are gathered in the flow chart of the figure 2. The first stage consists in acquiring the image to be treated by the means of a camera. Thereafter, we carried out detection by optical flow; segmentation of movements, and classification. The last stage represents the new approach for the detection of abnormalities in very dense scenes while being based on the speed and orientation of the individuals and that of the group. The various anomalies are detected by a fuzzy logic approach. The next stage is the tracking of the abnormalities. Finally a test is carried out in order to extract some comprehensible information (detection crowd behavior normal and abnormal).

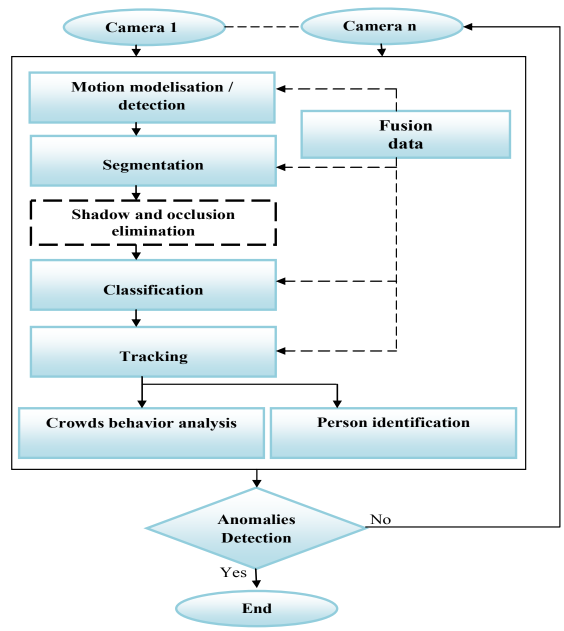

Fig. 2. General architecture of automated video surveillance system.

Our approach in this article relies on the new application which use the fuzzy logic in the case of division and fusion of the crowd. The detection of these behaviors will increase the speed of response of the security services in order to perform accurate analysis and detection of events in real time.

IV. MATHEMATICAL FORMULATION

A. Motion vectors extraction

The investigated crowd activities are characterized by movement of people. The examination of the motion dynamics of the crowd is based on the so-called motion vectors obtained by the methods described below. The optical flow is applied to each pair of subsequent video frames. Two stages of the processing can be distinguished, namely feature finding and feature tracking. The first stage is based on the corner detection algorithm proposed by Shi and Tomasi [16]. For each derivative pixel (defined? as the second partial derivative of the intensity of the original image) with surrounding K, the autocorrelation matrix $M(x,y)$ is calculated. Good corners occur in the points, where the smaller of two eigenvalues of the matrix $M(x,y)$ is greater than a predetermined threshold value. The set of feature points (corners) for the video frame is obtained in this step.

Tracking of the dislocation of the detected corners in the subsequent frame is done with the Lukas-Kanade algorithm [17], [18]. As a result, the second set of points is produced. Connecting corresponding points in subsequent frames provides the vector. It describes the motion of the/a detected feature point. If the position of the feature point in consecutive frames differs then the motion of that point is considered. The obtained vectors are then assigned to classes according to magnitude and direction. In the present work the classification is done according to the magnitude criteria only.

Optical flow analysis returns a set of motion vectors in the form:

$$V_{i,t} = (x_{i,t}, y_{i,t}, m_{i,t}, \theta_{i,t}) \quad (1)$$

Where "$V_{i,t}$" is the motion vector "i" at frame "t", represented by the feature point at the coordinate $(x_{i,t}, y_{i,t})$, the magnitude "$m_{i,t}$" and the orientation angle "$\theta_{i,t}$".

B. *Application of fuzzy logic*

Classical logic is a part of mathematics relatively well known to the public. It is on its principle that computers, computers and most digital machines work. In classical logic, decisions are binary: either true or false. It is on this point that fuzzy logic will be distinguished from classical logic. In fuzzy logic, a decision can be both true and false at the same time, with a certain degree of belonging to each of these two beliefs.

In our work we use fuzzy logic as a method of automatic classification of crowd behavior.

For example, consider these two rules of inferences:

- ✓ If the behavior is below threshold, then it is normal;
- ✓ If the behavior is more than threshold value, then it is abnormal.

In classical logic, an object can only be near or far. If the distance of behavior is less, then this one will be normal. In fuzzy logic, however, the object will be both normal and abnormal at the same time. Here, the object that is less than will, for example, is normal to 60% and abnormal to 40%.

One realizes that in fuzzy logic, a fact no longer has a strict belonging to a belief, but a "fuzzy" belonging.

The objective of using fuzzy logic makes it possible to reason not on numerical variables but on linguistic variables, that is, on qualitative variables. The reasoning on these linguistic variables will allow being able to manipulate knowledge in natural language. All that one has to return to the detection system are rules of inferences expressed in a natural language. For this work we will use the representation of the following linguistic values (figure 3):

C. *Events detection*

In this section, we describe the detection of anomalies in a dense scene. The scenarios chosen are part of the events described in the video [32]. The detected behaviors are two: Merging and splitting behavior: The question is whether groups of people meet or separate. To do this, we calculate the circular variance $S_{0;f}$ relative to the displacement orientations of the groups in each image f according to equation (2):

$$S_{0;f} = 1 - 1/n_f \sum_{i=1}^{nf} \cos\left(X_{i,f} - \overline{X_{o,f}}\right) \quad (2)$$

Where $\overline{X_{o,f}}$ is the mean angle of the groups in the image f defined by equation (3) :

$$\overline{X_{o,f}} = \arctan \frac{\sum_{i=1}^{nf} \sin(X_{i,f})}{\sum_{i=1}^{nf} \cos(X_{i,f})} \quad (3)$$

The circular variance S represents the dispersion of the groups. It is between 0 and 1 inclusive. $S_{0;f}$ Is 0 for a set of identical angles and is 1 for a set of totally opposite angles. We can then infer a fusion or division event from the value of $S_{0;f}$.

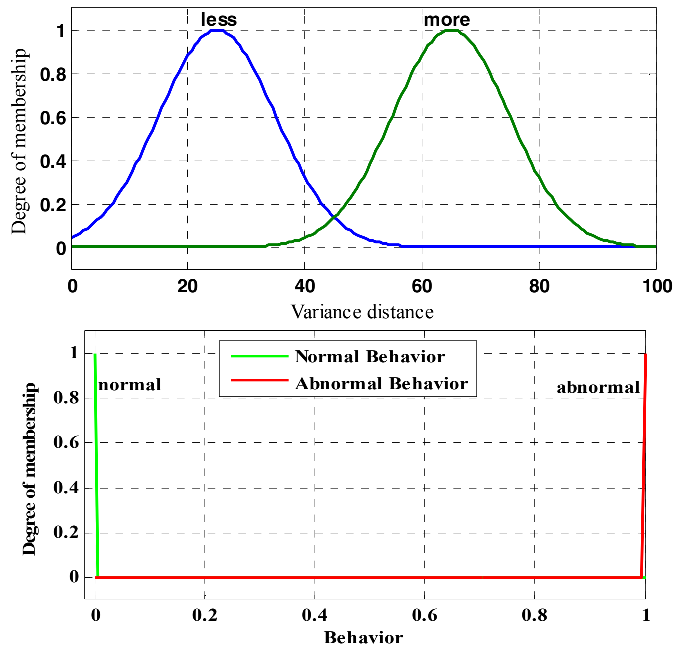

Fig.3. Image of linguistic values or fuzzy logic.

V. RESULTS

The proposed approach is based on computing the magnitude of the motion vector which presents the optical flow in the Cartesian frame. The point $P(x,y)$ is the position of his interest point at time t where $Q(x,y)$ is the position of the same point at $t+1$. We use the Euclidean distance to compute the distance travelled by the interest point:

$$M_i = \sqrt[2]{(Q_{xi} - P_{xi})^2 + \left(Q_{yi} - P_{yi}\right)^2} \quad (13)$$

This method is very useful when confronted with systems that are impossible, or difficult to model. Similarly, this method is very advantageous if one possesses a good level of human expertise. Indeed, it is necessary to provide to the fuzzy system a whole set of rules expressed in natural language to allow reasoning and draw conclusions. The greater the human expertise of a system, the greater the ability to add inference rules to the system of detection.

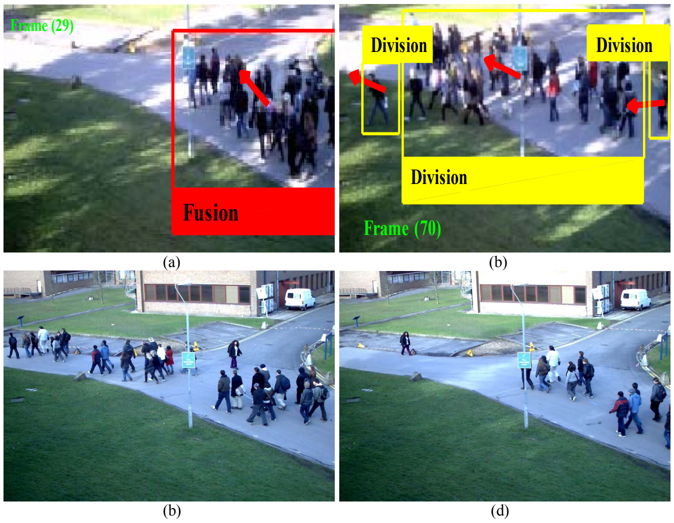

Fig. 4. Behavior analysis (a) Fusion (b, c, d) Division.

Fuzzy logic thus makes it possible to control complex systems that are not necessarily modelizable in an "intuitive" way figure 4. However, this method has various disadvantages. First, expressing one's knowledge in the form of natural language (and therefore qualitative) rules does not prove that the system will behave optimally. This method cannot guarantee that the behavior is precise or optimal, or even that guarantee that the rules entered by the programmer are not contradictory.

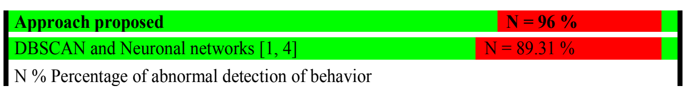

Fig.9. Crowd escapes behavior detection for several scenarios in the PETS2009 dataset. Our performance is compared with DBSCAN and Neural networks [1, 4].

For classification, we use fuzzy logic because each image has several classes for each category of events (division or fusion....). Although this makes the system more complicated, we have nevertheless the possibility of distinguishing the events related to the speed of crowd behavior. We divided the base of videos into several sets according to dated sets used. Some simulation results and the performances of the automatic control technique thus are presented in figure 5 [1, 4]. Our approach leads to better results for the three datasets used from the base of videos when the person is mobile.

VI. Conclusion

In conclusion, it can be said that fuzzy logic has the advantage of being intuitive and able to operate a large number of different systems with strong human expertise. Nevertheless, one should bear in mind that in fuzzy logic it is impossible to predict detection performance. If the settings are fine, the performance will be fine, but if there is a lack of precision in the settings, the performance will probably leave something to be desired. As prospects, we hope future work will implement on real-time maps and add some detection rules.

In spite of the disadvantages of logic fuzzy, in the future a hybrid technique may be used to try and avoid the problem of fuzzy rules. In such way can present tried to avoid the problem of the rules fuzzy.

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